ROBOT AFFORDANCE LEARNING WITH HUMAN INTERACTION

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ROBOT AFFORDANCE LEARNING WITH HUMAN INTERACTION

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To my mother, father, and brother,

who have supported me every step of the way

and without whom I could not have come this far.

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CHAPTER I

INTRODUCTION

1.0.1 Motivation

Many of the current tasks robots perform are trivial and already programmed in their systems. Modifying a robots ability to dynamically adapt learning through both human interaction and independent exploration can be helpful to various groups of people, such as elders needing assistance, students getting an education, and doctors needing medical assistants. The notion of learning from human interaction and acquiring skills is known as Socially Guided Machine Learning (SG-ML) [1]. Ideally, the robot will be able to learn from its environment and through human interaction in such a way that full guidance from humans is not necessary. In this research, my goal was to have Simon independently learn affordances of different objects in the environment and see how the learning benefited when the robot had human guidance. Using results of this research, more work can be done to have Simon use the human-guidance as a base for new exploration.

1.0.2 Overview of Work

In my research, my goal was to enable Simon the Robot, the robot in the Robotics and Intelligent Machines Center at Georgia Tech, to learn through both independent exploration and human interaction. I first made Simon learn affordances of objects by training over a set of examples and then using this data to predict affordances of new objects. For the independent learning scenario, he performed actions on all the possible configurations of each object, and then used this to create a classifier that would help him predict for future instances. Then, I added a human-guided condition in which objects were presented in a way that humans would naturally, based on previous work. The benefit of having this human guidance was that the examples were much more balanced in terms of positive and negative examples, leading to a more effective classifier. This way, the robots used the human guidance to enhance the learning. Results of this research replicated previous work in this area but on a different robot platform. Future work in this area can give more insight into how robots can take advantage of human help to improve their learning.

1.0.3 Previous Work

One of the main studies done in this area is by Maya Cakmak, who also studied robot affordance learning with human interaction with a different robot named Junior. She looked at how humans can help robots learn by conducting a user study and seeing how humans tended to teach. In the experiment, there were two different scenarios, the social and the nonsocial. In the nonsocial condition, Junior would be given all the different possible configurations of 5 objects and used those to train. In the social condition, the participants would decide how to teach the robot and were allowed as few or as many examples as needed. She found that humans tend to balance positive and negative examples, give more examples for more complex objects, start simple, taught one object at a time, gave more attention to rare affordances, and help the robot learn the goal.

Other researchers have conducted work related to this area by improving learning through observation, guidance, and exploration. For observation learning, researchers have made robots view a human demonstration and subsequently create a task representation. This particular way of learning allows robots to acquire skills, yet it requires the robot to learn in separate phases instead of learning in real-time [7]. Past works have also looked into learning through guidance. In this case, the robot does not learn unless the human guides it through the entire skill. Although this approach is more interactive, it usually requires the teacher to be an expert who knows how to teach skills to robots. In this research, the goal was to move towards getting non-experts to teach robots as well [6]. Lastly, researchers have analyzed learning through exploration, which is related to reinforcement learning. This method does not require humans to know the specifics of teaching the skill, but means that there is less interaction between the robot and human.

Other related work has looked into robot learning through human keyframe demonstrations [2], clarifying questions by the robot [4], and imitation and emulation of the human [5]. These past studies are similar in that throughout the learning process, the human has the same level of interaction. This means that either the human guides the robot through the entire task or the robot learns the skill by itself. In this research, two different ways of learning, independent and human-guided, were compared and using these results, robots can more effectively incorporate human-guided learning into its own learning to get the benefits of both.

CHAPTER II

IMPLEMENTATION

2.0.4 Research Platform

For this project, I worked with Simon the Robot, pictured below.

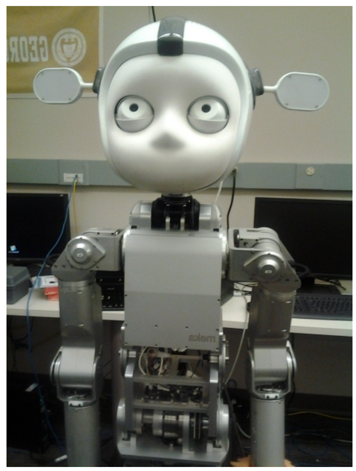

Figure 1: Simon the robot.

Simon is a humanoid robot used for social robotics research. His arms have 7 degrees of freedom and his hands have 4. The learning system that I worked with was called C6, which allows the robot to act based on sensory inputs. Many different sensors are used to provide Simon with information about the environment, including cameras and microphones. A view of the overhead camera that I used for sensing objects on the table is shown in Fig. 2. These sensors collect information as observations, which then get separated into percepts, based on different parts of the observation. For example, when an object is placed on the table, the overhead camera senses the object and each aspect of the object, like color or height, becomes a different percept. The perception system contains many of these percepts. Then, the belief system clusters percepts into meaningful objects, based on similarity metrics.

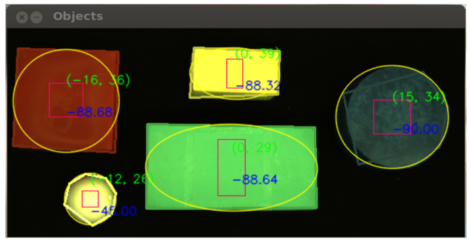

Figure 2: A view from the overhead camera.

For my project, I used location as a metric to combine percepts into beliefs. These beliefs were then used to identify the objects that Simon interacted with during the experiment.

2.0.5 Learning Framework

For this research, the learning problem was getting Simon to learn affordances of objects through several training examples and then using these examples to create a classifier that would predict affordances of new objects. In order to learn affordances, he performed two different actions, slide and grasp, on several objects and observed the result of performing that action. A slide action for Simon started with his hand 3 units from the side of the object and then ended after his hand moved 3 units past the location of the object. A grasp action started by moving down towards the object's location and ended after he closed his hand at that location. After observing the change in the object's state after performing the actions, he decided if the object was a slideable and/or graspable object. A set of training examples were conducted in this way, and a classifier was built to model the training set to help predict future examples.

To set up the learning framework for this problem, I created tuples that kept track of the states and action for each example. The tuples were stored in this format: <Initial state of the object, action performed, the final state of the object >. With this structure, all of the experiences can be saved so that machine learning algorithms can be applied to predict for future data. The action for this project was either slide or grasp, although more actions can easily be included into this framework. In order to decide whether an object was slideable and graspable, the initial and final states were used.

For slideable, if the distance between the final location and the initial location of the object was over some threshold, then the object was considered slideable. A reasonable constant value for this threshold was determined empirically.

For graspable, if the object disappeared in the final state, then the object was considered to be graspable. So, if the belief system contained no beliefs, then no objects were on the table, which meant that the robot had picked up the object successfully. Objects that failed to be graspable included objects that were too big to hold or objects that were in an orientation that made it hard to grasp.

2.0.6 State Machine

In order to control the flow of Simon's actions, I used a state machine, as shown below. For this project, I first had Simon start in the idle state, in which his arms are to the side. Then, after pressing a keyboard trigger, he moves his right arm to the ready state so that his arm is close to the table and ready to act on the first object.

At this point, the user can choose to either press s or g, which will prompt him to do a slide or grasp action, respectively. In each of these actions, he first goes into the BeforeLearningObjectState, which saves the initial state of the object. Then, it goes straight to the state that has Simon performing the appropriate action. Finally, it transitions to the AfterLearningObjectState, which saves the final state of the object. After this whole sequence finishes, Simon goes back to the ready pose and is ready to be commanded to perform another action. This state machine is a simple way to control Simon's actions and to guide him through the learning experiences.

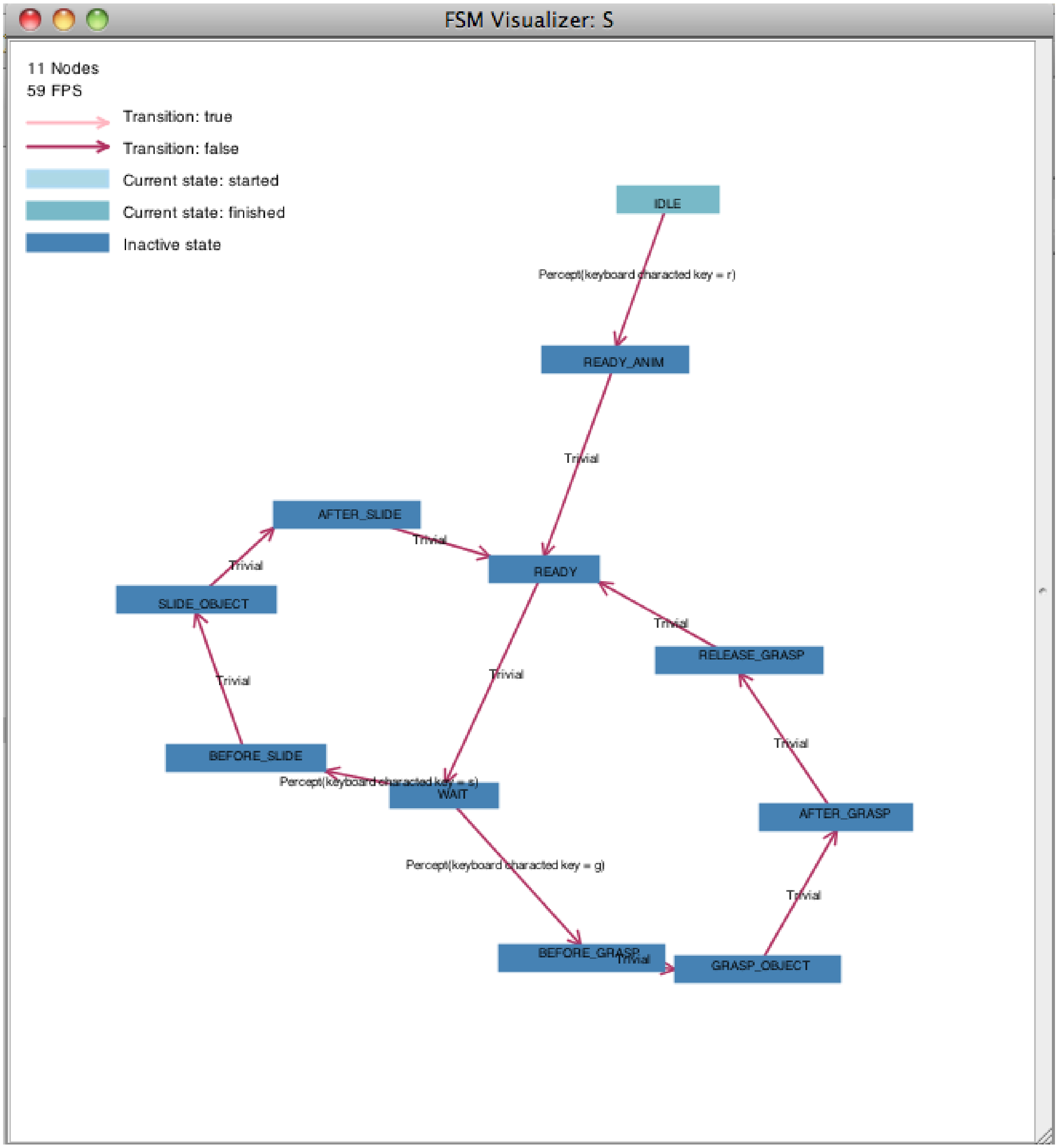

Figure 3: A snapshot of the state machine used in this project.

2.0.7 Support Vector Machines

For the machine learning aspect of this project, I used support vector machines (SVMs) to classify the training examples so that Simon could predict the testing examples using the SVM model. The features that I used for classificaton were: color, area, height, width, and location. I used SVMs because it maximizes the margin between the two classes, which is effective for classifying affordances. In this research, I used an SVM model for each affordance I looked at and had the classifier separate graspable vs. non-graspable. This way, when I presented a new object, based on its features, Simon would be able to use the SVM model from the training examples to classify the new instance.

2.0.8 Belief System and Percept Visualizer

For Simon to be able to interact with objects, I used the overhead camera to sense objects and the belief system to get all the data. As explained earlier in the research platform, the way the data flows through the system is the overhead camera first senses the objects on the table. These observations are stored in percepts based on the different aspects of the observation. For example, there is a percept for the location of the object as well as the color and the area. Then, based on a certain similarity metric, the percepts are combined to form beliefs. In this case, I used location as a metric to combine percepts with similar location into one belief that represents that object. This belief will contain all of the information about that object from the different percepts.

Fig. 4 shows a view of the percept visualizer. In this screenshot, there are a few different percepts activated. One of the main ones, colored in red in the picture, is the object percept, which means that at that current moment, the object percept is active. Within that percept, different attributes of the object, which are each represented by a different percept, are also activated, e.g., the brightness or the color.

These percepts are combined into beliefs, which are displayed in the belief window, shown in Fig. 5. This shows each belief and all of the data within it.

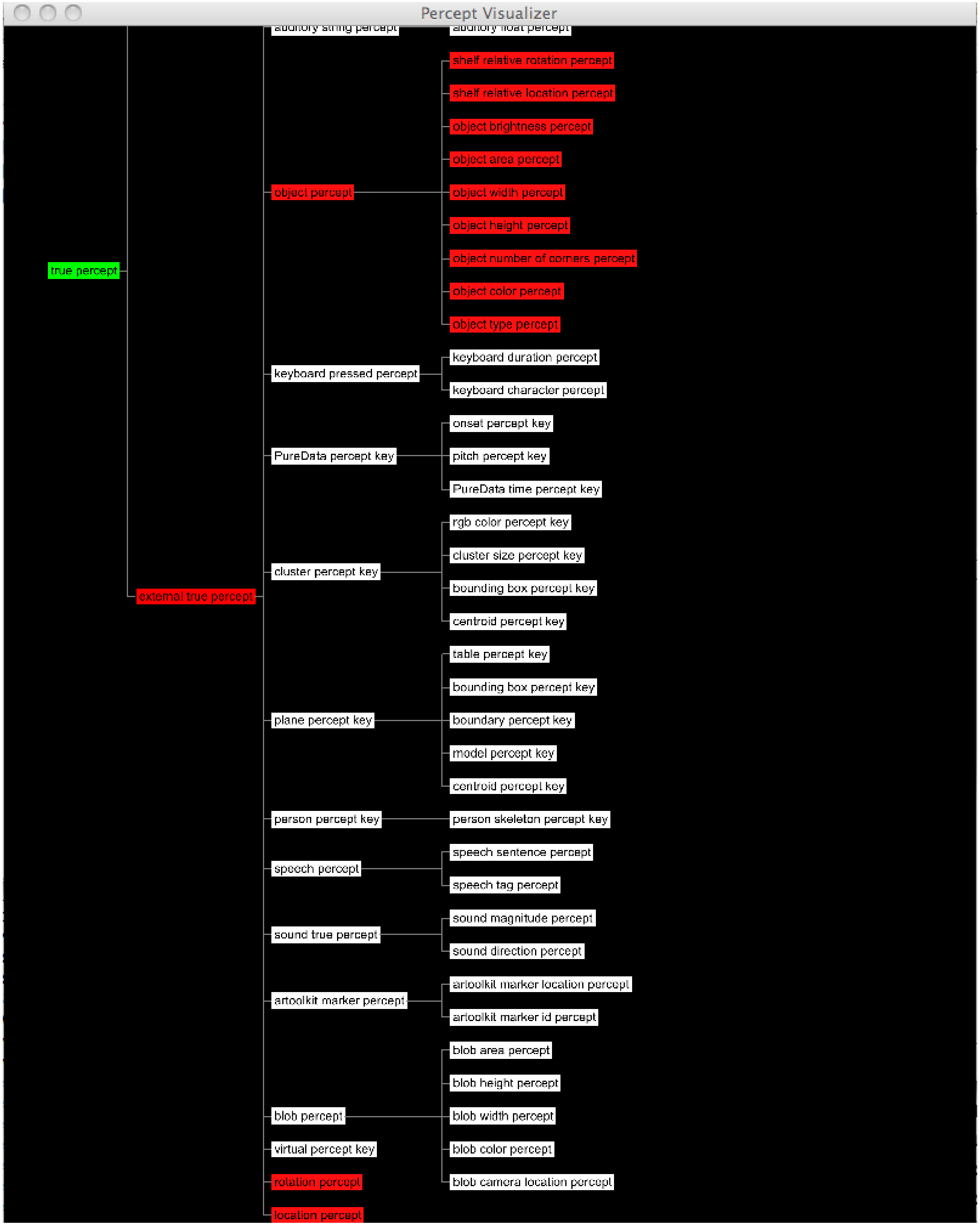

Figure 4: A view of the percept visualizer when an object is on the table.

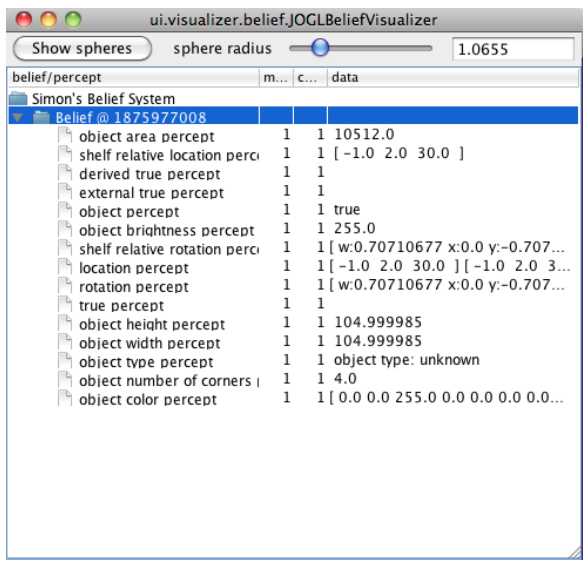

Figure 5: A view of the belief system when an object is on the table.

CHAPTER III

EXPERIMENT

To compare how Simon learns object affordances with and without human influence, I conducted a small study. In this experiment, I had Simon perform slide and grasp actions on 5 different objects displayed in Fig. 6. I had one sphere, one cube, and three different cuboids. The sphere and the cube had each one configuration. Two of the cuboids had three configurations and the last cuboid had two. Simon then worked with each of these 10 configurations. He had to learn the affordances of these objects through sliding and grasping each object.

Figure 6: Objects used in experiment.

For the experiment, I had 10 training examples and 5 testing examples for each of the 4 conditions stated below:

1. Slide and Systematic
2. Grasp and Systematic
3. Slide and Human-Guided
4. Grasp and Human-Guided

3.0.9 Systematic Condition

The systematic condition was when Simon tried all the possible configurations of each object. In this case, there were often more positive examples than negative or visa-versa. This is a condition that is known to cause problems in learning classifiers, including SVMs. This systematic condition represents Simon learning independently by trying every possible variant.

3.0.10 Human-Guided Condition

For the human-guided condition, the most ideal way to collect data would be to have user studies, but since it was not possible to conduct these studies, results from Cakmak's prior work were used to determine how humans usually teach. This was then used to give Simon objects in such a way that it models human teaching. Although Cakmak found several characteristics of how humans teach, like going from simple to complex or teaching one object at a time, these would not affect the way SVMs would classify since our SVM is not being trained in an online fashion but is given all examples for training at once. So, the only difference in the human-guided condition was that there was a balance of positive and negative examples. This meant I had 5 positive and 5 negative rather than a majority of either.

CHAPTER IV

CONCLUSION

4.0.11 Results

Comparing these two, systematic and human-guided, for both slideable and graspable, the results show that human-guided resulted in more accurate predictions by Simon. However, since there were only 5 testing examples, this was a small set of data and more tests need to be performed to confirm this result. The data is shown in Fig. 7. Also, in performing the different actions on these objects, results showed that

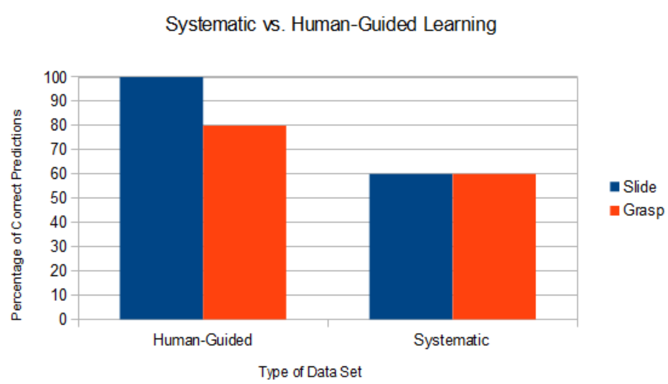

Figure 7: A graph of the results of the experiment.

4.0.12 Discussion

From the study that was conducted, the human-guided condition led to more accurate affordance predictions than the systematic. Although more tests do need to be performed, this does replicate the results of Cakmak that having human help can improve robot learning. In this experiment, the reason perhaps that the human-guided condition resulted in more accuracy is because having a balance of positive and negative examples can help the classifer find a more accurate line that divides the two classes. Especially with such a small set of data, it is imperative that each example helps the classifer find the line maximizing the margin. Thus, balancing positive and negative examples makes the classifier more effective.

4.0.13 Future Work

Future work on this project includes running user studies to analyze the way in which humans teach Simon. Although this was looked at for the Junior robot in a previous study, it would be interesting to look at how humans teach Simon since Simon has a lot of potential for more human interaction and more complex actions/tasks than Junior. Another extension of this research would be to add capabilities for Simon to not only get help from the human but respond back so that the interaction is more two-way. Simon could then ask the human for more clarification or provide the human with confirmation that it understood.

Also, previous research has not looked into having robots use humans as a base for learning to explore new possibilities. Extending this research, there could be three different cases to compare in Simon's affordancing learning, independent, human-guided, and then human-guided with exploration. In this new third condition, Simon would use the examples from the human-guided and then explore new objects that are similar to the training objects in most features. This way, Simon would be able to incorporate both human-guided and independent learning. This idea could be a useful extension of this research.

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Robot Affordance Learning with Human Interaction

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15 Pages

Directed by Professor Andrea Thomaz

Many of the current tasks robots perform are trivial and already programmed in their systems. Modifying a robots ability to dynamically adapt learning through both human interaction and independent exploration can be helpful to various groups of people, such as elders needing assistance, students getting an education, and doctors needing medical assistants. In my research, the goal was to compare how two different ways of learning, independent and human-guided, compared when a robot learned object affordances. This research can give insight into how robots can take advantage of human help to improve their learning.

My main goal was to have Simon independently learn affordances of different objects in the environment and see how the learning benefited when the robot had human guidance. I first had Simon perform several actions on objects, and I recorded the state of the object prior to the action, the actual action Simon performed, and the state of the object afterwards. The robot then used this data to predict the affordances of future objects. Once the robot was able to learn about its environment independently, I included human guidance in the second condition by presenting the objects in a way that humans would naturally, based on previous work. The benefit of having this human guidance was that the examples were much more balanced in terms of positive and negative examples, leading to a more effective classifier. To test this, an experiment was conducted in which Simon performed slide and grasp actions on 5 different objects. There were two conditions for each action, systematic, in which Simon tried all possible configurations, and human-guided, in which the examples were more balanced. Results showed that the human-guided condition resulted in slightly more accurate predictions than the independent, systematic condition.